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ERROR AND UNCERTAINTY ANALYSIS FOR ECOLOGICAL MODELING AND SIMULATION
1998 Annual Report (CS1096)

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ACTIVITIES (January 1998 to December 1998)

Literature Review

We conducted an extensive literature review in the fields of: a) soil erosion, b) spatially-explicit ecological and environmental modeling, c) error assessment and budget, d) GIS and remote sensing-based simulation, f) assessment of error under different temporal and spatial scales, g) error and uncertainty in plant community modeling, h) Army LCTA data i) RUSLE and WEPP models.

Selection of hardware and software packages

We acquired a number of software programs and manuals to assess their adequacy for our study. These are: S-plus, ArcView, and ArcInfo. Additionally, we purchased other software tools such as: Visual C++ and GSLib.

We purchased five personal computers to be employed for analysis and reporting.

We obtained membership in the GMS (Geographic Modeling Systems) Laboratory at the University of Illinois at Urbana-Champaign, where we have access to software programs such as GRASS.

We reviewed existing and widely used software packages for GIS, image analysis, and error and uncertainty assessment. We compared the compatibility, flexibility and cost of various systems. Finally, we selected ArcView GIS, Geographic Resources Analysis Support System (GRASS), and Geostatistical Software Library (GSLIB). ArcView was selected mainly because of its flexibility, wide use, and extensions for basic spatial and image analysis; GRASS to provide some special spatial analysis methods not found in ArcView; and GSLIB to carry out spatial variability modeling and simulation, and uncertainty assessment.

Wang participated in a supercomputer workshop at NCSA (National Center for Supercomputing Applications) at the University of Illinois at Urbana-Champaign.

Meetings and visits to case study site

We held numerous meetings with members of USACERL (US Army Construction Engineering Research Laboratories) to: familiarize ourselves with the case study; understand the needs of the Army; and discuss possible approaches of our analysis. CERL members participating in those meetings were: Alan Anderson and David Price.

Gertner and Parysow visited the site of the case study, Fort Hood. They had a chance to assess the erosion situation at that installation through direct inspection of the land and through contacts with personnel of this military base, and members of federal and state agencies involved in this subject. These included: a) at Ft. Hood: Emmet Gray (Chief of the Environmental Office); and Don Jones (Soil Conservationist); b) at NRCS (Natural Resource Conservation Service): Fredrich Schrank (Resource Conservationist); Wayne Gabriel (Soil Data Quality Specialist-Database); James Greenwade (Resource Soil Scientist-Team Leader); and Max Bircket (Geomorphologist); c) at Blackland Research Center (Texas A&M University Research and Extension Center): Dennis Hoffman (Research Scientist, Water Quality Group); and June Wolfe III (Assistant Research

Scientist, Water Quality Group); d) at The Nature Conservancy of Texas: Laura Sanchez (Senior Field Botanist). Additionally, Gertner and Parysow helped collect vegetation samples for a project headed by Terry McClendon and Michael Childress (both form The University of Texas at El Paso), and David Price (USACERL).

We visited the Natural Resources Conservation Service office in Temple, Texas to discuss aspects of the soil survey currently employed for calculating the soil erodibility factor "K". Additionally, we familiarized ourselves with the proposed work to make compatible the soil surveys from the two counties Fort Hood is located on.

We collected 576 soil samples at Fort Hood as a part of the effort to assessing and reducing uncertainty of the soil erodibility factor "K". Available soil surveys and geostatistical methods will be employed for that purpose.

Publications

Parysow and Gertner completed and submitted to the journal "Ecological Modelling" a paper dealing with comparison of ecological scenarios with process models accounting for uncertainty in model components. The title of this article is "The Role of Interactions in Hypothesis Testing of Ecological Scenarios with Process Models". This paper has been accepted for publication. They in conjunction with Jim Westervelt wrote another paper dealing with building error budgets for large and computationally-intensive process models. The title of that article is "Efficient Approximation for Building Error Budgets for Large and Computationally-Intensive Process Models". This work was presented in a modeling of complex systems conference in New Orleans in July, and has also been submitted to "Ecological Modelling". SERDP support is acknowledged in both manuscripts.

In addition, below are other papers in preparation where SERDP is acknowledged:

Gertner, G.Z. ; S. Fang and J.P. Skovsgaard 1998. A Bayesian approach for estimating the parameters of a forest process model based on long-term growth data. Ecological Modeling (In review).

Gertner, G.Z. and S. Fang 1998. Estimation of a highly nonlinear biological growth model using Bayesian estimation with rejection sampling. In review The American Statistician (In review).

Data

We obtained data from numerous sources concerning the case study at Fort Hood. These data include: precipitation, soil, topography, vegetation, impact of military training, and conservation measures. We are in the process of making these data compatible and usable in our analyses.

GENERAL FRAMEWORK FOR ERROR AND UNCERTAINTY ASSESSMENT

Objectives

The main objectives of this project are a) to develop a general methodology for conducting sensitivity and uncertainty analysis and building error budgets in simulation modeling over space and time; and b) to apply that methodology to the assessment of soil erosion through the RUSLE caused by military training at Fort Hood, Texas. This methodology includes:

1) characterizing the source of prediction errors and their spatial and temporal distributions
2) partitioning of errors into various components
3) providing guidelines for error management and error reduction

Methodology and framework

A GIS-based methodology is being developed for making spatial and temporal predictions, uncertainty analysis, and error budgets. Figure 1 shows the outline of the approach as applied to the RUSLE prediction system, whereas Figure 2 emphasizes the flow of data and operations. Thus, a grid-based database is generated employing field data, as well as auxiliary data from digitized elevation models, digital soil maps, digitized aerial photos and satellite images. Data calculation and analysis are carried out to derive values for the input factors, and predictions made for all sampling plots. Values for non-sampled locations are predicted mainly using geo-statistical methods.

In addition, the optimal operational scale for the prediction is determined through the scaling-up method (Atkinson and Curran 1997). Thus, pixel values of the data layers are aggregated to the optimal operational scale level. Spatial and temporal predictions are made at the optimal operational scale. Spatial sensitivity of the input parameters on the prediction is analyzed mainly through Monte Carlo based methods (Figure 3) (Benkobi 1994, Lane & Ferreira 1980, McKay et al. 1978, Merier et al. 1971, Risse et al. 1993). In addition to Monte Carlo, sensitivity analysis is carried out using deterministic methods at different area scales. Different sensitivity analysis approaches and importance measures may be compared in order to find the best one in terms of cost-efficiency.

Sources errors are assessed in the GIS-based prediction system (Lanter and Veregin 1992, Lunetta et al. 1991, Walsh et al. 1987). Errors arise mainly from data, material, operations, modeling, and inherent fuzziness of the real world. In this study, error sources of input parameters and prediction can be divided as follows: data errors, data process errors, modeling and classifying errors. Within each group, the error sources are further divided into sub-groups. The error sources, propagation, and accumulation are described in Figure 4. Figure 5 explains error propagation in layer-based GIS as proposed by Lanter and Veregin (1992). Error measurement indices are error measures selected for quality assessment of GIS operators. The error vector of three error indices, such as spatial error, thematic error, and temporal error can be used for each of data layers in GIS.

Spatial and temporal variability, as well as the local and spatial uncertainty of the input parameters and predictions of soil loss are mainly derived and assessed using geo-statistical methods. These methods include ordinary and indicator kriging, sequential Gaussian simulation and indicator simulation (Deutsch and Journel 1998, Goovaerts 1997). These geo-statistical methods are compared based on the spatially derived estimates and uncertainty measures such as error variance maps and probability maps of soil loss exceeding a given tolerance value T. In addition, the stratification based method (Wang 1996, Wang et al 1997) and multivariate interpolation by regularized spline with tension (Mitasova and Mitas (1993) are also being tested for comparison with the geo-statistical methods.

The error propagation and accumulation through all GIS operations are conducted through Monte Carlo simulations (Emmi and Horton 1995, Openshaw 1989, 1992, Openshaw et al 1991). The error propagation for data layer scaling up and overlaying are also made by calculating error variances and co-variances of the data layers, formulating their propagation and deriving the composite error variance (Cola 1997, Veregin 1989, 1992). The error budget and partitioning into various sources are then worked out by applying the methods developed by Gertner et al. (1995, 1996), that is, Taylor series based error propagation equations, and combination of Monte Carlo simulation and orthogonal response surface model. Table 1 displays how the error budget partitions error by sources. Finally, strategies for error and reduction are being analyzed as well.

As a case study, we are developing a GIS-based methodology to make spatial and temporal predictions, analyze uncertainty, and build error budgets of soil erosion status based on the RUSLE applied to military training. In this methodology, we generate a grid-based database containing a digitized elevation model, and soil, rainfall, and vegetation maps. Spatial and temporal predictions of soil loss are made at different optimal operational scales. Using sensitivity techniques, spatial sensitivity of the input parameters on the prediction is analyzed. Various source errors are configured and assessed. The error modeling for the specific operations (data layer scaling up and overlay) is made by calculating error variances and covariances of the data layers, formulating their propagation and deriving the composite map error variance. Based on mean and variability estimates of environmental conditions, relationships between training intensity and disturbance, and the uncertainty information obtained, we predict spatial distribution of probabilities of disturbance that would be caused by the scheduled training intensity. The error budget for the whole population or a homogeneous sub-area is worked out by applying the Monte Carlo approach and orthogonal response surface model. In addition, spatial error distribution and patterns are identified and quantified using geostatistical techniques.

Background - The RUSLE and case study

The Universal Soil Loss Equation (USLE) was developed to empirically predict soil loss due to erosion caused by water (Aldrich and Slaughter 1983, Kuss and Morgan III 1980, 1986, Thomas et al. 1967, Weltz et al., Wheeler 1990, Wischmeier 1976, Wischmeier and Smith 1965, 1978). The equation quantifies soil erosion as the product of six factors: rainfall and runoff erosiveness, soil erodibility, slope length, slope steepness, soil cover, and support conservation practices. This equation has recently been revised into the Revised Universal Soil Loss Equation (RUSLE) (Renard et al 1991, 1997). The model system is described by the following equation, which is widely used for predicting soil erosion:

$$A = R \bullet K \bullet LS \bullet C \bullet P \qquad (1)$$

Where A = the computed spatial and temporal average soil loss per unit of area; R = rainfall-runoff erosivity factor; K = soil erodibility factor; LS = the slope length (L) and steepness factor (S); C = cover factor; and P = support practice factor.

The Army Training and Testing Area Carrying Capacity model (ATTACC) (SERDP Project CS 1102, Alan Anderson, USACERL) is used by the military to determine training carrying capacity, and evaluate the impact of alternative training exercises. This model was developed according to the Evaluation of Land Value Study (ELVS), and is intended to provide operation and support costs of Land Rehabilitation and Management (LRAM) accounting for environmental, training, and economic factors (Siegel 1996). Training carrying capacity is determined by the following relationship between land condition, disturbance caused by military training and natural recovery:

$$\begin{bmatrix}\text{PREDICTED LAND}\\ \text{CONDITION (LC)}\end{bmatrix} = \begin{bmatrix}\text{CURRENT LAND}\\ \text{CONDITION}\end{bmatrix} + \begin{bmatrix}\text{CHANGE IN LC DUE}\\ \text{TO TRAINING LOAD}\end{bmatrix} + \begin{bmatrix}\text{CHANGE IN LC DUE TO}\\ \text{NATURAL LAND RECOVERY}\end{bmatrix}$$

The Revised Universal Soil Loss Equation (RUSLE) is applied to predict the change in land condition (characterized as soil loss) caused by training. Spatial and temporal variability of the input parameters for rainfall, terrain, soil and vegetation results in spatial and temporal variability of soil loss. Additionally, estimation errors of various sources, as well as model uncertainty will be propagated through the system into the predicted value. In turn, partitioning of the error in the predictions according to the error source may be conducted through error budgets. Additionally, it is very important that decision-makers know not only the sensitivity of the prediction to error in input parameters, but also how the inherent and operational errors propagate and accumulate through the system, as well as how the errors vary spatially and temporarily. To that end, a model is needed for quantifying errors and reporting the resulting uncertainties. In fact, making predictions without analyzing the associated uncertainty may mislead decision-makers as to the quality and reliability of those predictions.

We have initiated uncertainty assessment for the rainfall erosivity factor (R) of the RUSLE model in Fort Hood, Texas. Currently, a single value of the "R" factor is obtained from published isoerodent maps, which is assumed to be constant for the whole installation. One approach to assessing the uncertainty of that method would be to compare the values provided by that isoerodent map with actual values obtained from rainfall recording station in Texas. An alternative approach to obtaining “R” values, aimed at reducing uncertainty, will be implemented as well. That approach would consist of spatially extrapolating the values obtained from those recording stations using geostatistics and assigning uncertainty to the estimated points. For that purpose, we obtained 15-minute rainfall data from a database collected by the National Climatic Data Center (NCDC), which is appropriate for soil erosion studies.

We analyzed uncertainty and error propagation in prediction of slope length and steepness (LS) factors involved in the revised universal soil loss equation (RUSLE) in the case study area (Fort Hood). We acquired data and material for conducting this study, including LCTA and DEM data. Statistical analysis were carried out as well. Different prediction equations of LS factors have been used and compared. The uncertainty and error propagation from models, sampling, measurement errors and spatial variation of input variables are being studied with two methods: 1) combination of Kriging interpolation and Taylor series, and 2) Monte Carlo based sequential Gaussian simulation. In addition, we completed testing of the GIS program GRASS, and the geo-statistical software package GSLIB.

We began analyzing the soil erodibility factors (K factor) as reported in the NRCS (Natural Resources Conservation Service) soil surveys, so as to assess their associated uncertainty. Additionally, we obtained soil sampling data from USACERL for comparison with the information provided by the NRCS soil surveys.

We began exploring how to incorporate the work conducted by Steve Warren and Helena Mitasova (SERDP-funded project) to improve the description of topographic features.

We tested existing RUSLE (Revised Universal Soil Loss Equation) software packages, and studied the possibility of integrating those programs with an error analysis tool to be developed in our project.

We began studying the structure of the plant community sub-model of FHASM (Fort Hood Avian Simulation Model) developed by USACERL. We are evaluating the possibility of employing this model to simulate plant community in conjunction with the RUSLE

We developed a parameter estimation method based on Bayes inference and rejection sampling for nonlinear models (including uniresponse and multiresponse models); and a random number generator for highly correlated non-normal distributions.

Results of uncertainty analysis for the LS factor

Preliminary studies for uncertainty and error propagation in prediction of slope length (L) and steepness (S) factors of the Revised Universal Soil Loss Equation (RUSLE) have been conducted for our case study area, Fort Hood. We acquired data and material for this study (LCTA and DEM data), and also conducted statistical analysis. Different prediction equations for the LS factor were used and compared. The spatial uncertainty and error propagation from models, sampling, measurement errors and spatial variability of input variables were studied using combinations of ordinary kriging, indicator kriging, sequential Gaussian and indicator simulation, and Taylor series based error propagation. These methods were further compared based on uncertainty measures including error variances of spatial prediction values and probability maps of prediction values exceeding a given soil loss tolerance threshold.

Table 2 shows descriptive statistics of the LS factor from 219 field plots. Steepness (S) and slope length (L) were measured in the field at three different locations within each plot, at 0, 50 and 100 m along the 100 m transect line. The mean gradient (SM) and slope length (LM) were calculated for each plot and the average LS factor value was derived using the set of LS equations involved in the RUSLE. It was found that slope length had the largest coefficient of variation, but very low correlation with steepness and LS factor, and also that steepness was highly correlated with LS factor. On the other hand, the distributions of all the three variables possessed long and skew tails towards the right. Comparison of LS factor values from the RUSLE and USLE was is shown in Figure 6. Employing the USLE led to higher LS factor values than employing the RUSLE, and this difference increased as LS factor values increased. These differences are comparable to those found by Moore and Wilson (1992).

The left side of Figure 7 shows the smooth histogram of 219 plot data for steepness and LS factor. Because the distributions had significant skewness, logarithmic scaling was used to normalize them. The scatter-plot indicates the high linear correlation between S and LS factors. The right side of that figure shows the location of sample data for the LS factor, whose values are represented by different colors.

The spatial variability of the three variables (steepness, slope length, and LS factor) was studied using semivariograms and standardized indicator semivariograms in three directions: omnidirection, NE-WS and SE-NW. The semivariogram model parameters of the three variables are shown in the lower part of Table 3, whereas the standardized LS factor indicator semivariogram model parameters in the upper part of the same table. The semivariograms were fitted with the same spherical model, but with different values of the parameters for nugget (C_0), sill (C_1), and range (a). The basic model is:

$$\gamma(h;z_k) = C_0(z_k) + C_1(z_k)Sph\left(\frac{h}{a}\right) \qquad (2)$$

$$Sph\left(\frac{h}{a}\right) = \begin{cases} 1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3 & if \quad h \le a \\ 1 & otherwise \end{cases} \qquad (3)$$

Where h is the lag, and z is one of the three variables, S, L, and LS factor. The subscript k means the indicator and thus z_k is the cutoff value.

Figure 8 shows the change of standard deviations with increasing number of realizations of LS factor. From 1 to 30 realizations, the standard deviation decreases quickly, becoming stable from that point on. Therefore, 30 realizations could be used for LS factor simulation. Figure 9 compares three methods based on their LS factor estimates: ordinary kriging (OK), indicator kriging (IK), and sequential indicator simulation (SISIM). All the methods share a common feature: sample data values are honored at their locations. The spatial distributions of the estimates are also similar in terms of location of the LS factor values. However, outside of the sampling area, ordinary and indicator kriging produced LS factor values of zero. Also, the two kriging methods produced smoothed estimate maps, whereas the simulation method did not and, therefore, spatial variability is more detailed. Furthermore, kriging methods often underestimate the values at locations where there is high soil loss. Thus, smoothed and underestimating maps may not be suitable in applications sensitive to the either presence of extreme values or patterns of spatial variability.

Figure 10 and 11 display uncertainty maps for the estimates in terms of error variance and probability of LS estimates larger than 1.0. The kriging methods had minimum local error variance, which is especially clear on the error variance map by ordinary kriging. However, ordinary kriging creates error variance dependent only on local data configuration and not on actual data values. Smoothing increases as estimated points are located farther away from the data locations. On the other hand, the conditional variance created by indicator kriging does not depend only on the local data configuration, but also on the local actual data values. Thus the LS conditional variance map by indicator kriging shows improved spatial variability and local uncertainty. However, the drawback from smoothing was not eliminated in that approach. An answer to that problem may be found in the sequential indicator simulation method, which produces a conditional variance map and spatial variability pattern that are closer to reality than indicator kriging.

Another important feature is that both indicator kriging and sequential indicator simulation methods gave probability maps for LS factor values larger than a given threshold value, such as 1.0. This feature is very useful for decision-makers that schedule training exercises, since high probability areas for soil loss exceeding a given tolerance value can be easily found on the probability maps. Additionally, it should be noted that unlike indicator kriging, the probability map obtained by the sequential indicator simulation does not depend on the local data configuration. This simulation method provides a visual and quantitative measure (actually a set of indicator covariance models) of spatial uncertainty. Spatial features, such as specific strings of large values, are deemed certain if seen on most of the L simulated maps. Conversely, a feature is deemed uncertain if seen only on a few simulated maps. Also, total cost and probability of wrong decisions may be derived by combining a loss function and the economic cost of declaring an area in need of recovery. Finally, although not listed here, results have also been obtained for slope length (L) and steepness (S).

LAND MANAGEMENT SYSTEM (LMS) AND UNCERTAINTY ASSESSMENT

Spatial-temporal models are widely used for assessment and decision making in natural and cultural resources. DoD has invested millions of dollars in developing hundreds of models and simulators to help conserve and maintain its over 25 million acres of land that are essential for critical readiness training and testing. In 1995 the Defense Science Board emphasized the importance of using modeling and simulation in natural and cultural resource assessment and management to achieve cost-effective military training and testing objectives.

The main goal of the LMS is to develop techniques and software programs for simulation modeling aimed at effectively executing the mission of military land managers and trainers as well as managers of civil works facilities. These capabilities are expected to support the priorities established in both military and civil works natural resource management.

The modeling issues addressed by LMS include: threatened and endangered species (TES) and biodiversity, land-based carrying capacity for training, land rehabilitation and erosion control, and establishing an ecosystem approach to the management of training areas. Through models and simulations, land managers should be able to assess the potential effect of a management action on the environment. The idea behind this strategy is to maximize mission use while minimizing impact on ecosystems and available resources.

Specifically, the goal of LMS R&D is to provide the means for efficiently integrating a broad array of land management modeling tools. This task includes addressing issues such as: modeling platforms, process-based models, decision support systems and data requirements to the modeling systems. Ultimately, LMS is expected to achieve its mission by allowing managers to:

1) maximize training/testing flexibility
2) sustain landscapes for future mission use
3) meet a dramatically increasing number of environmental mandates

The quantification and implications of uncertainty associated with these models and simulators have not been explicitly considered in a comprehensive manner. Hence, DoD needs to develop a comprehensive framework for quantifying, analyzing and managing uncertainty of modeling and simulation results. It is clear that consideration of the errors associated with LMS modeling tools will greatly improve the effectiveness of this system. In fact, a thorough assessment of the errors involved in this effort will provide vital information regarding the level of uncertainty of modeling results. This in turn will inform decision-makers not only about the reliability of the decisions made according with those results, but also about efficient ways of improving that reliability. The project on error assessment and management is also contributing to the LMS coordinated effort among the USACE labs and other DoD units by creating opportunities to leverage resources for achieving common goals. Likewise, this project is expected to enhance installation support through the incorporation of these techniques into the integrated Training Area Management (ITAM) Program.

COORDINATION WITH ORNL

The University of Illinois (UI) will work on the general framework for the assessment of all sources of modeling errors and uncertainty using the error budget approach. The UI as a case study will be working directly with the Natural Resources Assessment and Management Division at USACERL on the Army Training and Testing Area Carrying Capacity model (ATTACC) (SERDP Project CS1102) and the Terrain Modeling and Soil Erosion Simulation (SERDP Project CS752-93) at Fort Hood.

In parallel with the UI work, ORNL (Ecological Modeling and Simulation Using Error and Uncertainty Analysis Methods (CS1097), Dr. Anthony King) will concentrate on certain types of spatial uncertainties and stochastic uncertainties as it relates to threatened and endangered animal (avian) populations. As a case study, ORNL will work on a habitat and spatially structured demographic model, Terrestrial Migrant Model (TMM) (SERDP Project CS758). They decided that they would calibrate the model at Fort Hood for black-capped vireo and golden-cheeked warbler. They will conduct error and uncertainty assessment based on this model.

There are many types of uncertainties as it relates to such avian populations that are similar to the uncertainties found in ATTACC, but because of the mobility of such populations, there are many differences. This is particularly so in terms of certain types of spatial uncertainties and methods for assessing these uncertainties. Although the UI will explicitly consider spatial uncertainties in their case study with ATTACC, ORNL work will be an important component in the overall error budget work. ORNL work will complement the UI work since spatial uncertainty will be one of the many sources of error the UI will need to consider in the general error budget framework. Through out the project, the UI will work with ORNL to incorporate their results into the general error budget approach. Both groups working at Fort Hood will facilitate this process. Also, to promote the process, the UI group plans to meet three to four times a year with the ORNL group. We plan to meet next December in Washington at the SERDP Technical Symposium and Workshop, in March at Fort Hood, in May in Washington at the SERDP Annual Review, and in September at an unspecified location.

TABLES

Table 1. A partition of final prediction variances and errors.

Error sources	Prediction variances %	Prediction errors %
Data errors		
Sampling error		
Measurement error		
Geometric error		
Digitized error		
……		
Sub-total		
Data process errors		
Rounding		
Transformation		
Geometric rectification		
Image overlapping		
……		
Sub-total		
Experimental design error		
Sub-total		
Model and classification errors		
Component 1		
……		
Component n		
Classification 1		
……		
Classification n		
Prediction errors		
Prediction value error		
Spatial error		
Human error		
Total		

Table 2. Descriptive statistic of LS factor field measurements (SM, LM, LSM mean the steepness, slope length and LS mean of three different measuring locations for a field plot).

	SM	LM	LSM		SM	LM	LSM
Mean	4.742694	38.05175	0.686401		Correlation		
Stds	6.534919	27.30394	1.295366	LM	-0.06935		
Variation %	72.57465	139.3636	52.98896	LSM	0.944361	0.038154	
Maximum	62.66667	166.6667	15.8393				
Median	3	28.33333	0.379486				
Minimum	0.33334	7	0.076243		Covariance		
Mode	3	100	0.796208	SM	42.51016		
Kurt	32.97782	2.929024	87.66725	LM	-12.3171	742.1008	
Skew	4.939896	1.624935	8.180085	LSM	7.957619	1.343298	1.670312

Table 3. Parameters of semivariogram models.

Standardized LS factor indicator semivariogram models						
Indicator k	LS value	Probability	Nugget C_0	Sill	C_1	a
1	0.10	0.1	0.85	1.0	0.15	110
2	0.16	0.2	0.58	1.0	0.42	30
3	0.21	0.3	0.87	1.0	0.13	70
4	0.26	0.4	0.92	1.0	0.08	60
5	0.33	0.5	0.72	1.0	0.28	50
6	0.40	0.6	0.72	1.0	0.28	40
7	0.48	0.7	0.60	1.0	0.40	30
8	0.69	0.8	0.37	1.0	0.63	20
9	2.05	0.95	0.55	1.0	0.45	70
Non-standardized steepness (S), slope length (L)and LS factors semivariogram models						
	S		8.0	44	35	60
	L		100	800	700	40
	LS		0.2	2.3	2.1	60

FIGURES

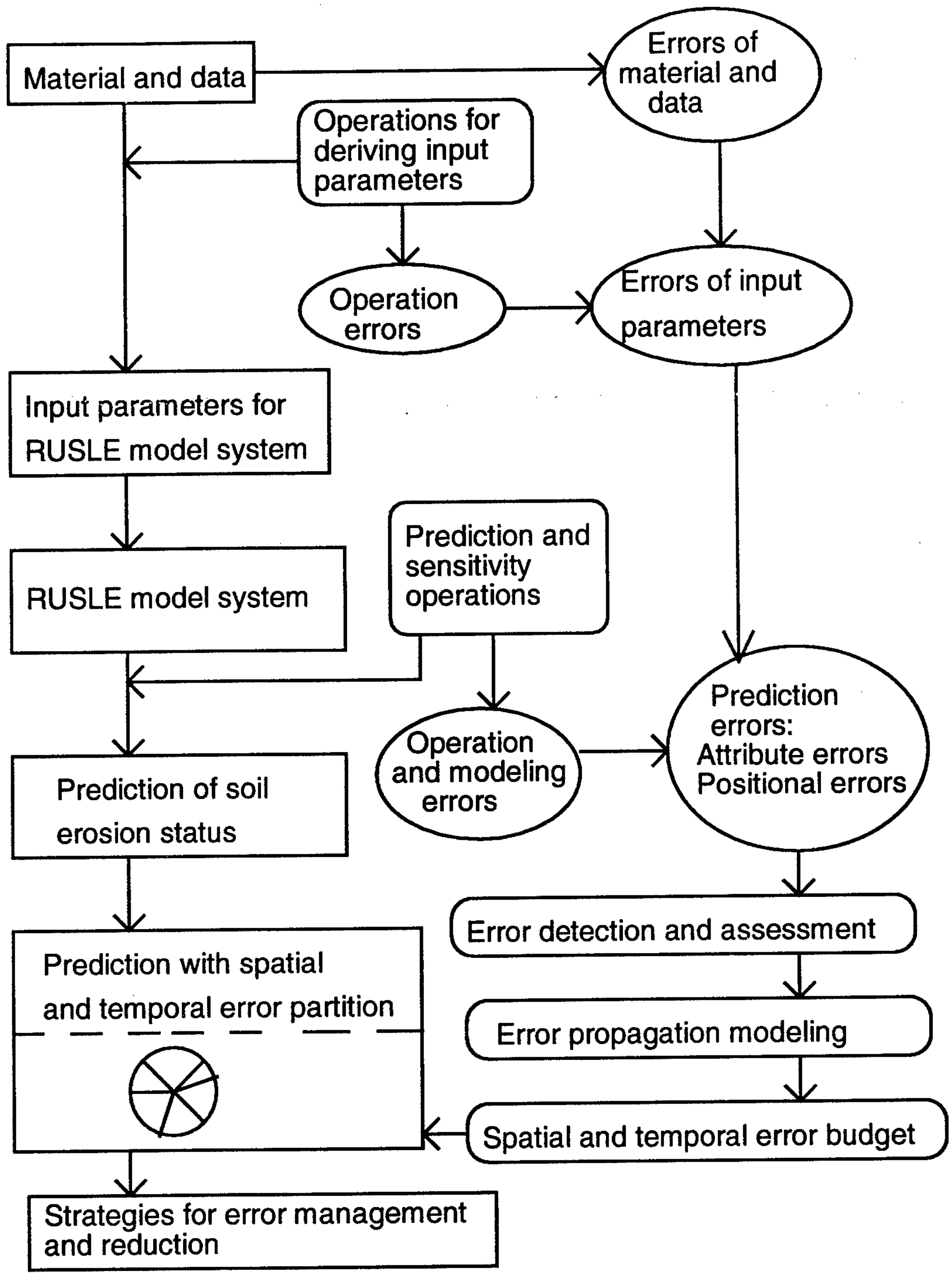

Figure1. The general description of the methodology for soil erosion status prediction, uncertainty analysis and error budget of RUSLE system.

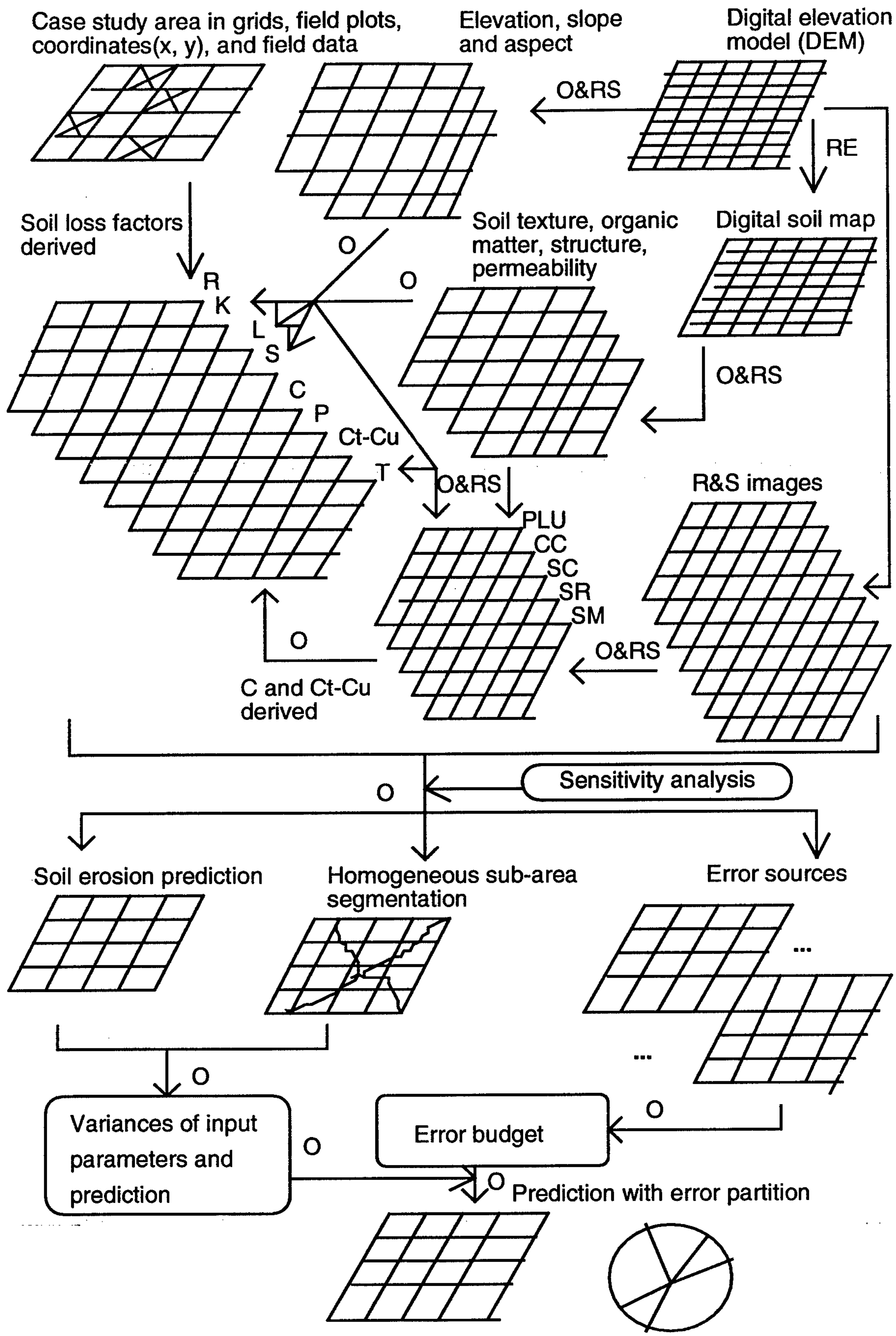

Figure 2. Flow of GIS-based prediction, uncertainty analysis and error budget of soil erosion status (O = operations of image process and statistic, RS = re-sampling, RE = rectification, R&S = remote sensing).

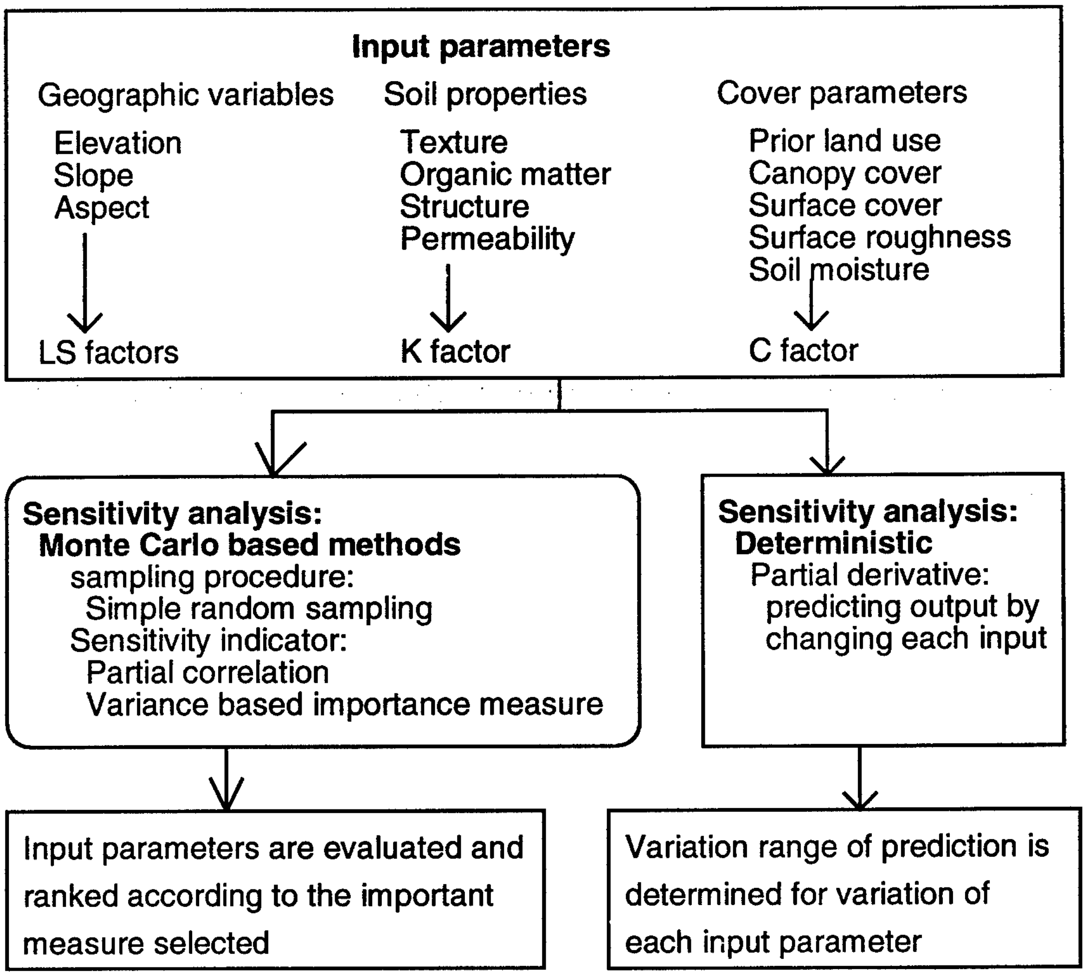

Figure 3. The sensitivity analysis of input parameters on soil erosion status prediction.

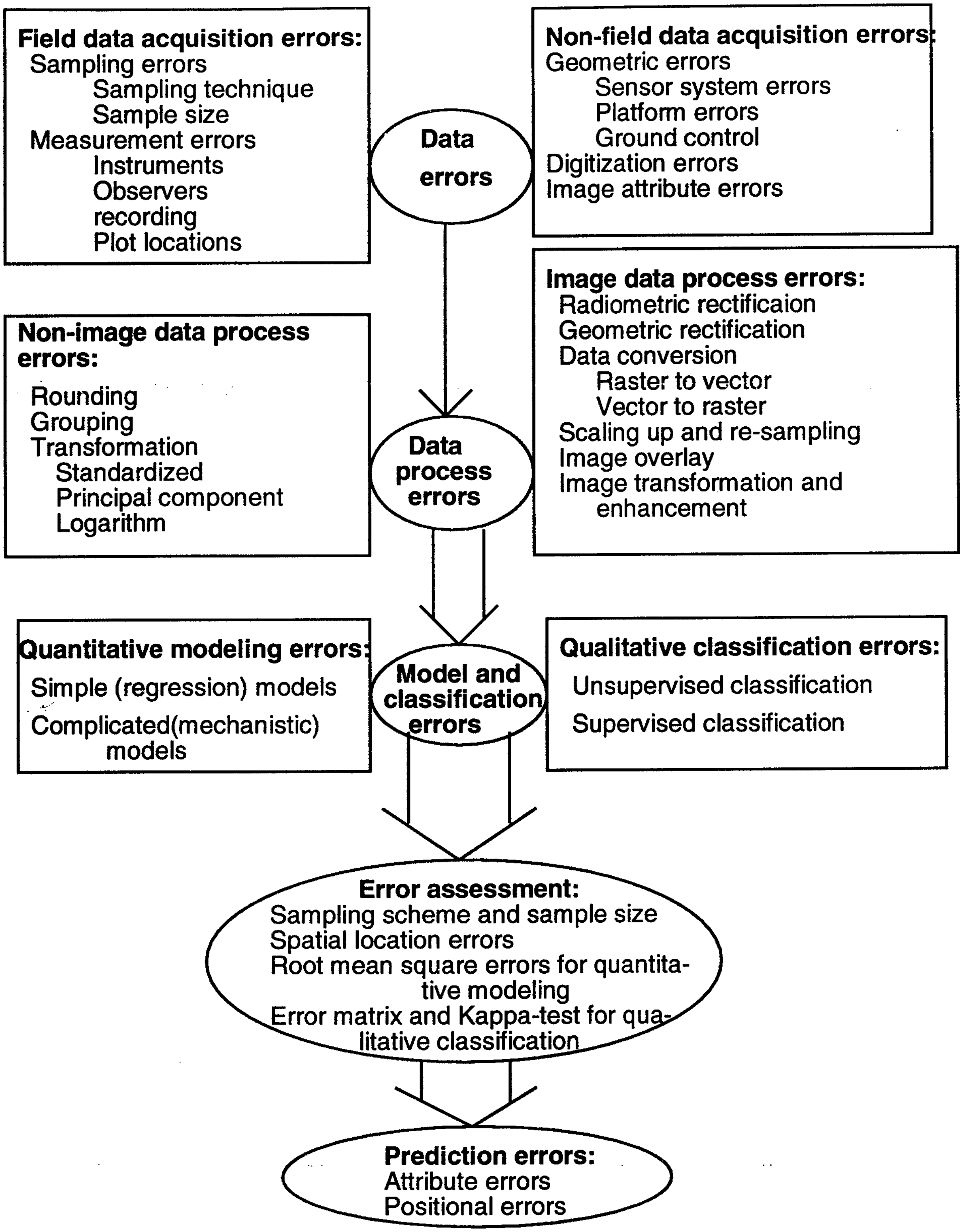

Figure 4. Error sources and propagation of soil erosion status prediction system.

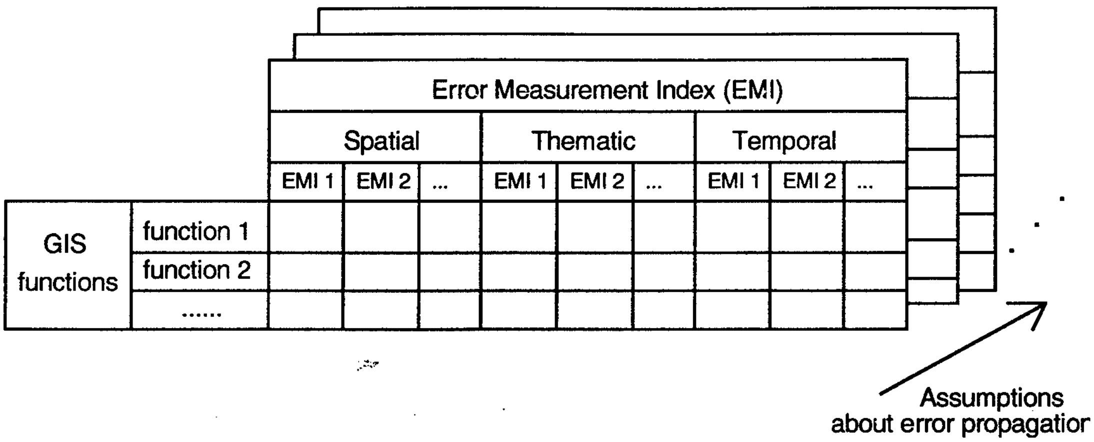

Figure 5. Conceptual error propagation in layer-based GIS. Each cell in the matrix references a specific error propagation function designed to propagate a specific error measurement index (column) through a particular GIS function (row) based on a set of assumptions about error propagation (plane). (Lanter & Veregin 1992).

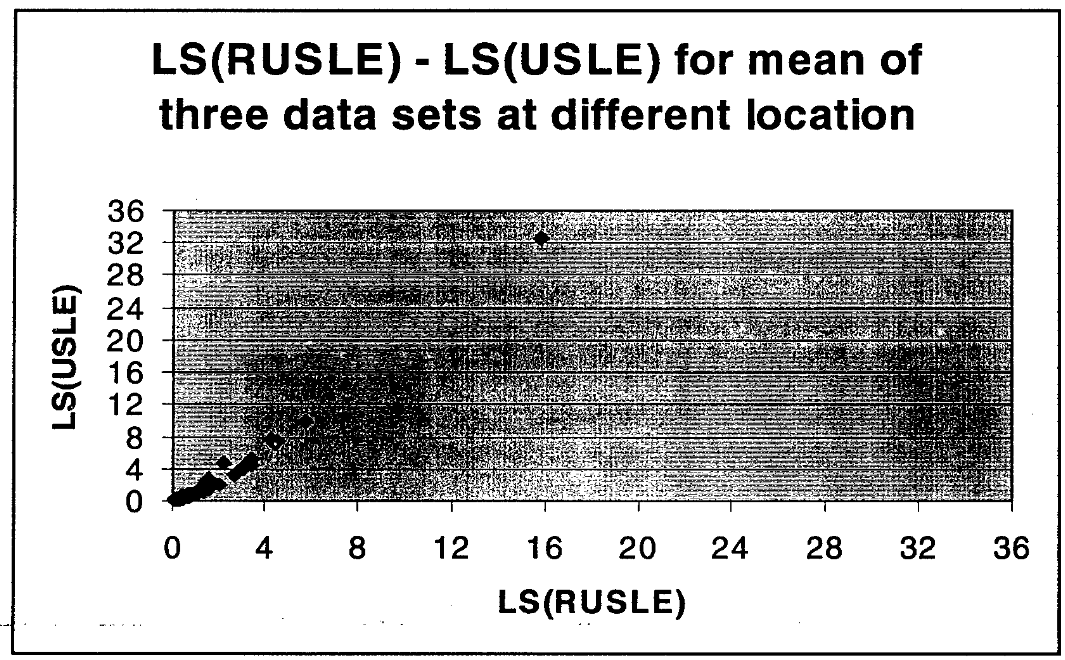

Figure 6. Comparison of field plot LS values calculated using RUSLE and USLE systems.

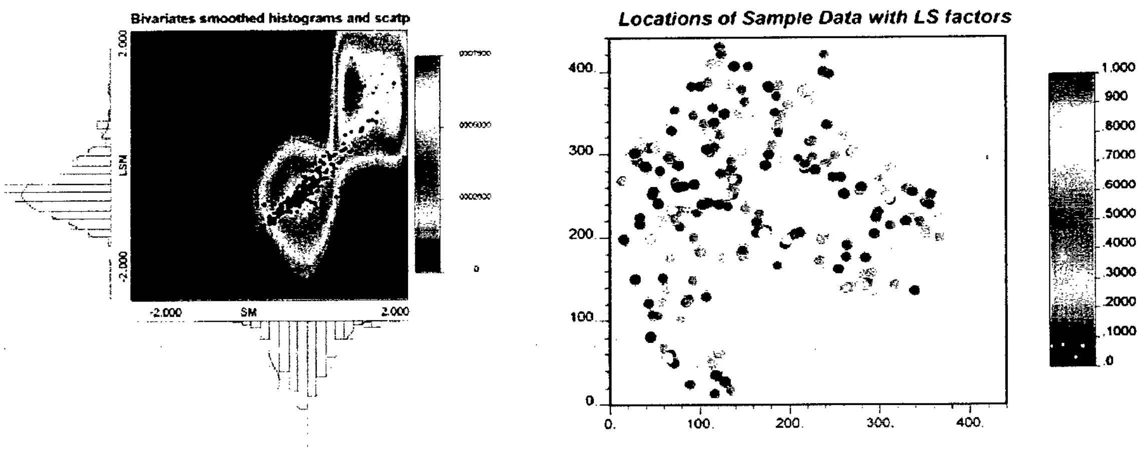

Figure 7. Smoothed histogram (left) of LS factor and steepness, and scatter plot, and location of sample data (right).

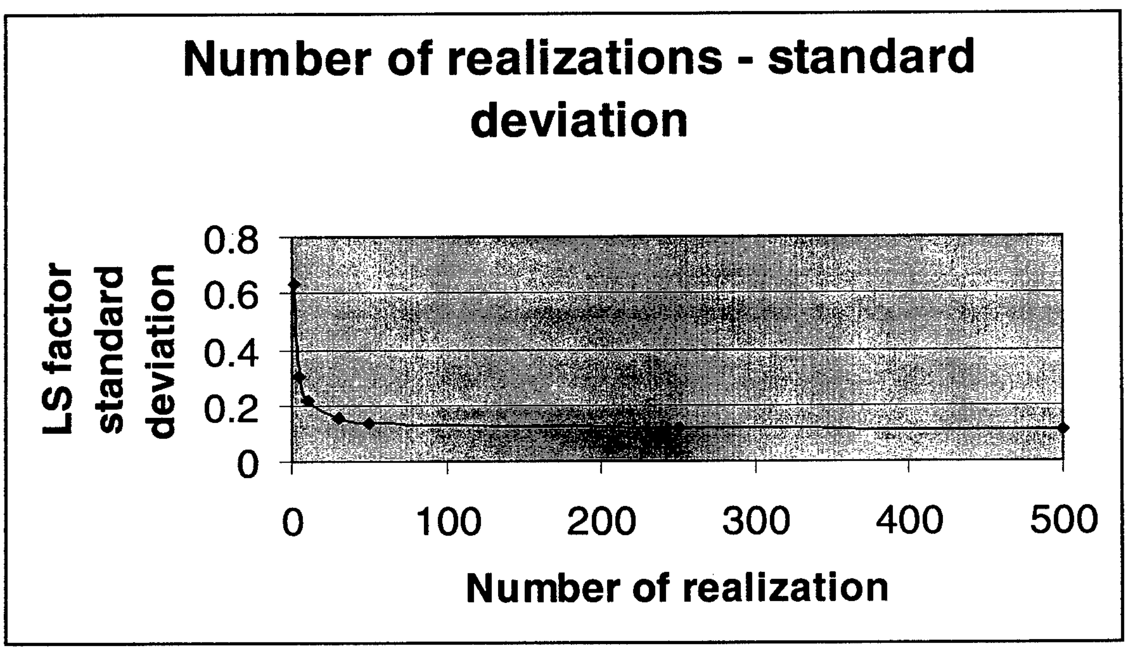

Figure 8. Change of standard deviation with increasing number of realizations for LS factor simulation.

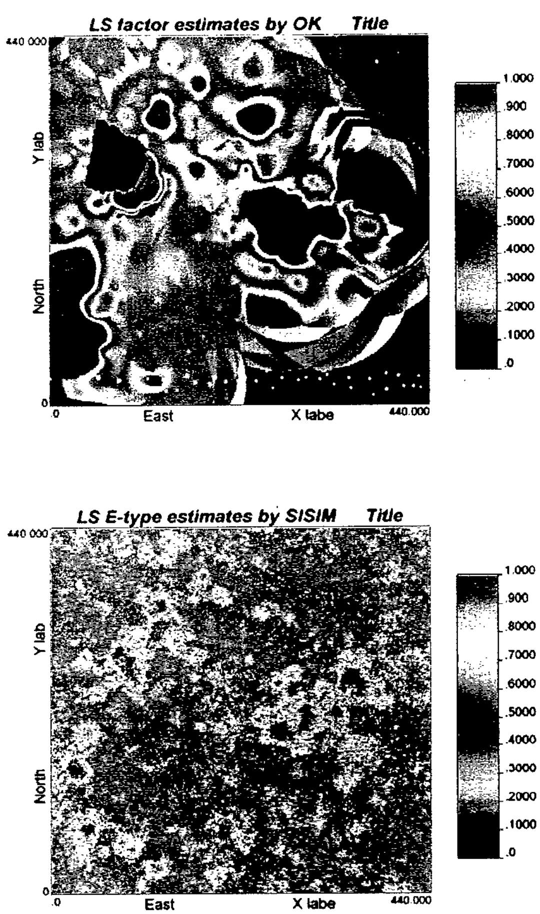

Figure 9. Comparison of different methods based on estimates.

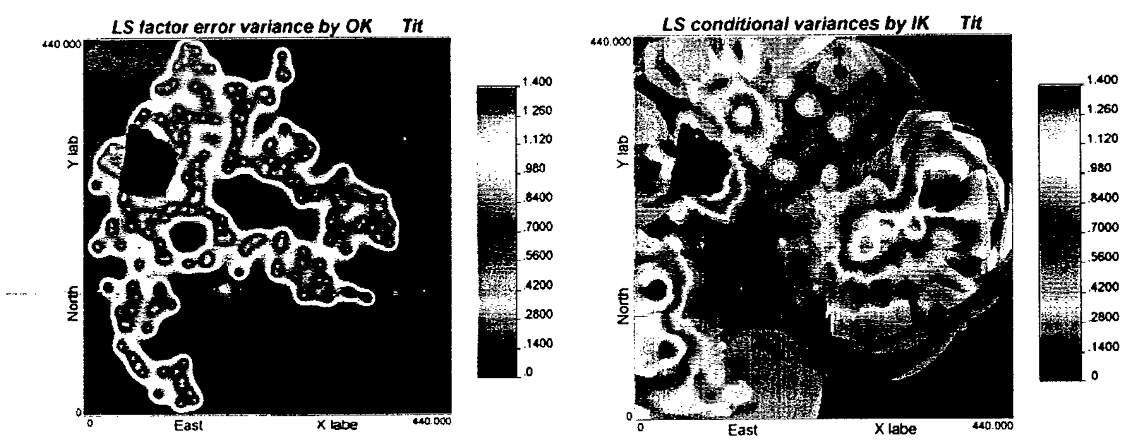

Figure 10. Comparison of different methods based on error variances.

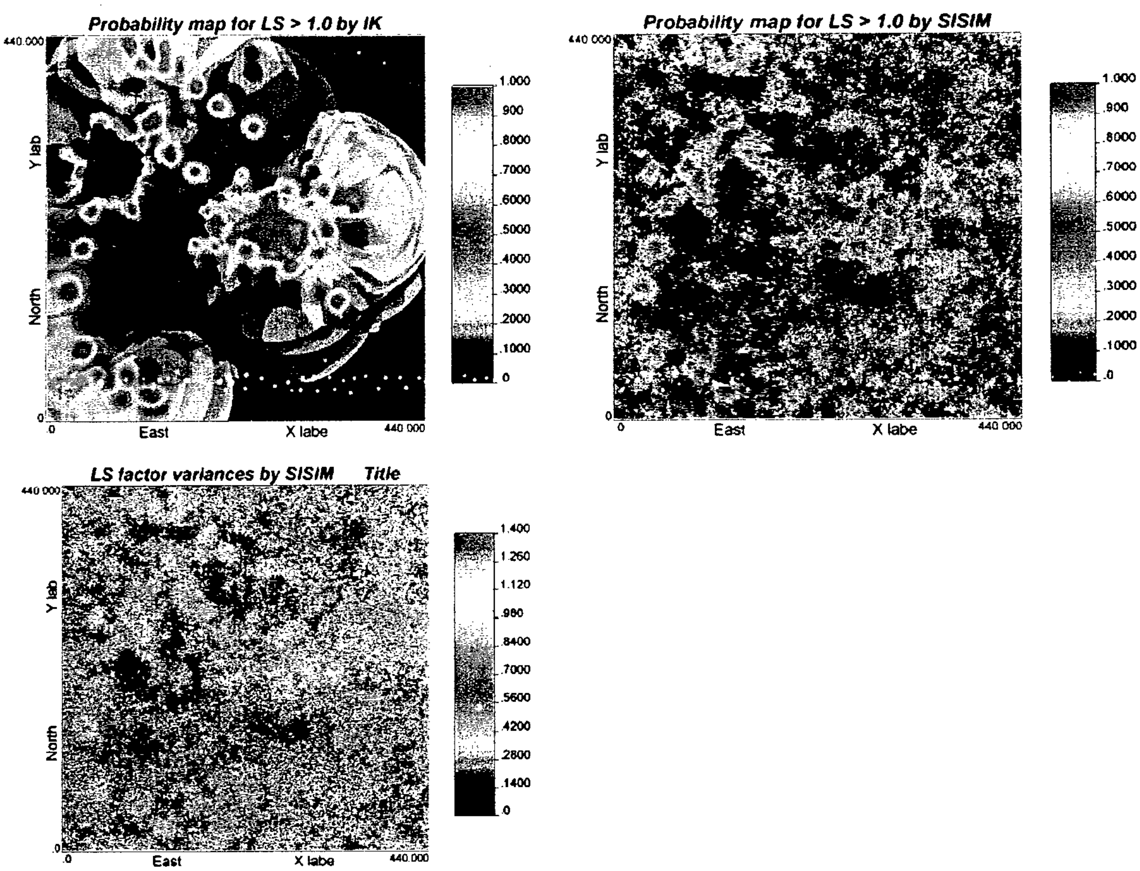

Figure 11. Comparison of different methods based on probability maps of LS factor exceeding a given tolerance threshold value.